2008

A new framework for urban sustainability assessments: Linking complexity, information and policy

Moira L. Zellner
University of Illinois at Chicago, mzellner@uic.edu

Thomas L. Theis
University of Illinois at Chicago, theist@uic.edu

Arunprakash T. Karunanithi
National Risk Management Research Laboratory, Karunanithi.Arunprakash@epamail.epa.gov

Ahjond S. Garmestani
U.S. Environmental Protection Agency, garmestani.ahjond@epa.gov

Heriberto Cabezas
National Risk Management Research Laboratory, cabezas.heriberto@epamail.epa.gov

Computers, Environment and Urban Systems 32 (2008) 474–488

Contents lists available at ScienceDirect

Computers, Environment and Urban Systems

journal homepage: www.elsevier.com/locate/compenvurbsys

A new framework for urban sustainability assessments: Linking complexity, information and policy

Moira L. Zellner [a,*], Thomas L. Theis [b], Arunprakash T. Karunanithi [c], Ahjond S. Garmestani [c], Heriberto Cabezas [c]

[a] University of Illinois at Chicago, Department of Urban Planning and Policy (MC 348), 412 South Peoria Street, 2nd floor, Chicago, IL 60607-7065, USA
[b] University of Illinois at Chicago, Institute for Environmental Science and Policy (MC 673), 2121 West Taylor Street, 5th floor, Chicago, IL 60612-7260, USA
[c] US Environmental Protection Agency, Office of Research and Development, National Risk Management Research Laboratory, 26 W. Martin Luther King Drive, Cincinnati, OH 45268, USA

ARTICLE INFO

Keywords:
Agent-based modelling
Fisher Information Index
Urban sustainability
Environmental assessment

ABSTRACT

Urban systems emerge as distinct entities from the complex interactions among social, economic and cultural attributes, and information, energy and material stocks and flows that operate on different temporal and spatial scales. Such complexity poses a challenge to identify the causes of urban environmental problems and how to address them without causing greater deterioration. Planning has traditionally focused on regulating the location and intensity of urban activities to avoid environmental degradation, often based on assumptions that are rarely revisited and producing ambiguous effects. The key intellectual challenge for urban policy-makers is a fuller understanding of the complexity of urban systems and their environment. We address this challenge by developing an assessment framework with two main components: (1) a simple agent-based model of a hypothetical urbanizing area that integrates data on spatial economic and policy decisions, energy and fuel use, air pollution emissions and assimilation, to test how residential and policy decisions affect urban form, consumption and pollution; (2) an information index to define the degree of order and sustainability of the hypothetical urban system in the different scenarios, to determine whether specific policy and individual decisions contribute to the sustainability of the entire urban system or to its collapse.

1. Introduction

Cities are spatial patterns that persist in time, in which no single constituent remains in place (Holland, 1995). Urban systems emerge as distinct entities from the complex interactions among social, financial, and cultural attributes, and information, energy, and material stocks and flows that operate on different temporal and spatial scales. Urban environmental problems (e.g., air pollution, open space fragmentation and excessive fuel consumption) create the pressing need for urban sustainability. Such complexity poses a challenge to identify the causes of urban environmental problems and how to address them without causing greater deterioration. Environmental planning has traditionally addressed these problems with policies regulating the location and intensity of urban activities, often based on assumptions about urban and environmental dynamics that are rarely revisited (Alberti, 1999; Chin, 2002; Ewing, 1994, 1997; Neuman, 2005). Given the complexity of urban systems and the environment that supports them, the key intellectual challenge of urban sustainability is a fuller understanding of the dynamic spatial interactions among the components of the coupled urban-environmental system. Such understanding can inform urban decision-makers of the environmental consequences of responding to urban needs.

We seek to contribute to this understanding by developing an assessment framework with two main components. The first includes the development of a simple agent-based model of a hypothetical urbanizing area that integrates data on spatial economic and policy decisions, energy and fuel use, air pollution emissions and assimilation. We use our model to test how different residential preferences and landscape characteristics shape the development of urban areas, in turn affecting energy use and pollution patterns, and how different policies can affect this relationship. The second component of our assessment framework involves

* Corresponding author. Tel.: +1 312 996 2149; fax: +1 312 413 2314.
E-mail addresses: mzellner@uic.edu (M.L. Zellner), theist@uic.edu (T.L. Theis), Karunanithi.Arunprakash@epamail.epa.gov (A.T. Karunanithi), Garmestani.Ahjond@epamail.epa.gov (A.S. Garmestani), Cabezas.Heriberto@epamail.epa.gov (H. Cabezas).

0198-9715/$ - see front matter © 2008 Elsevier Ltd. All rights reserved.
doi:10.1016/j.compenvurbsys.2008.08.003

defining the stability, degree of order and sustainability of the hypothetical urban system using information theory and indexes that can explain the system-wide states and trends. This integrated framework enables us to make meaningful comparisons among urban scenarios, adding to the existing array of sustainability assessment tools, such as the ecological footprint, life-cycle analysis, and integrated land-use transport GIS models (Deakin, Mitchell, Nijkamp, & Vreeker, 2007 provide a summary of some of these methods). The specific contribution of the proposed framework is that it explicitly connects policy, decentralized decision-making and environmental quality, and analyzes both temporal and spatial trends of these interactions. In this manner, scholars and policy-makers can explore how policy influences behaviour, the impact of such behaviour on environmental variables, and whether this impact contributes to the sustainability of the entire urban system or to its collapse.

Our paper also seeks to question and clarify the assumptions about the relationship between specific land-use patterns and energy use and concentration of pollutants. Empirical findings are inconclusive (Alberti, 1999; Garde, 2004; Neuman, 2005), suggesting not that either position is necessarily wrong, but that this relationship may be nonlinear or may vary with the scale of analysis. For example, increases in density support energy efficiency by shortening trips and reducing household energy requirements. Beyond a certain area size, however, high urban densities generate negative externalities due to congestion and concentration of pollutants beyond the environment's assimilative capacity, while low densities allow for pollution dispersion. This observation depends on the scale of measurement, however. Low densities may be accommodated in different layouts, e.g., uniformly distributed or clustered in multiple centres, which may significantly affect energy use and pollution. While the density is equally low at a regional scale in both scenarios, the local high densities in the second layout support the decentralization of activities and shorter trips. In contrast, the first layout imposes longer distances and lower household energy efficiency, resulting in overall higher energy consumption and congestion, more so if trip destinations are located outside the region and if densities are such that public transportation modes cannot be supported. The implications for policy are different in each scenario, as the justification for intervention varies to reflect the different market failures (congestion versus distortions of transportation costs and land prices).

Finally, we also seek to expand the suite of metrics that can help gauge the sustainability of an urban system in its present state, or possible future states as behaviour, technology and policy change. While agent-based models can provide a variety of spatial and temporal output measures computed at different scales, we seek to illustrate the multi-dimensional insights that can be derived when they are combined with a new dimension of impact that accounts for the long-term sustainability and stability of the entire system based on the outputs of the agent-based model. Such combination of multiple dimensions can give a clearer picture of the consequences of specific policies and individual behaviours, as the various scales of impact are evaluated together.

In sum, the purpose of our paper is to illustrate how the integration of agent-based modelling and the Fisher Information Index can help identify policy and behavioural lever points to improve environmental quality, test the assumptions about how urban form relates to environmental quality, and provide multi-dimensional assessments of complex urban-environmental systems. The next section describes the components of the agent-based model we developed to address these questions, followed by the simulation results from different policy and behavioural scenarios and their analysis with Fisher Information Index. We conclude with general observations about urban sustainability based on the various measures and about the applicability of this assessment framework to specific urban areas.

2. The basic USAFE model

We present a generic agent-based model, the Urban Sustainability Assessment Framework for Energy (USAFE), which draws from urban economics and environmental science and planning to represent the land-use decisions and consequent energy consumption and pollution dynamics in an urban system. We chose agent-based modelling over other spatial modelling tools because our research questions require the analysis of forces and behaviours originated in, and modified by, the interaction of heterogeneous landscapes and actors operating at different spatial and temporal scales. The explicit representation of socio-economic, political and natural processes in space and time and the feedback mechanisms connecting them, makes agent-based modelling useful to examine the inevitable uncertainties in complex multi-dimensional systems that other methods have more difficulties in handling (Parker, Manson, Janssen, Hoffman, & Deadman, 2003).

Since the 1990s, there has been considerable activity in various applications of cellular and agent-based modelling to spatial processes, in particular models of land-use and land-cover change (e.g., Brown & Robinson, 2006; Caruso, Rounsevell, & Cojocaru, 2005; Deadman, Robinson, Moran, & Brondizio, 2004; Ducrot, Le Page, Bommel, & Kuper, 2004; Hanley & Hopkins, 2007; Hoffman, Kelley, & Evans, 2003; Parker & Meretsky, 2004; Rand, Zellner, Riolo, & Fernandez. Fernandez, 2002; Torrens, 2006; Yin & Muller, 2007; Zellner, 2007). This research has mostly focused on the drivers of change and the effects of policy on the process of change. Some have focused on biophysical impacts, such as effects on forest cover and water sustainability, but not on energy use and emissions. Other modelling approaches that address energy use and air pollution have focused on forecasting pollution from traffic, constructing regression models and indicators that relate urban form to energy consumption due to travel patterns, and spreadsheet models that compute aggregate levels of emissions based on energy use in alternative energy-management scenarios (Affuma, Browna, & Chanb, 2003; Guindon & Zhang, 2007; Sadownik & Jaccard, 2001; van de Coevering & Schwanen, 2006). While policy-relevant, these models do not address the type of decision-making that drives the broader land-use and transportation processes affecting air quality. Several spatially-explicit models have been developed that integrate the broader land use and transportation dimensions (e.g., TRANUS, UrbanSIM, CURBA). Of these, only TRANUS considers emissions from transportation. These are highly sophisticated models that are conceived as forecasting rather than exploratory tools for policy evaluation. Their sophistication, however, requires extensive data for inputs and calibration, and makes it difficult to relate the processes to the outputs. In particular, land-use and energy-use decisions are implicit in the models, and yet these decisions are at the core of complex environmental problems in urban areas. With USAFE, we attempt to make the connection between decisions, policies and environmental outcomes explicit and transparent. The purpose of USAFE, then, is to test the effect of various corrective land-use, infrastructure and resource management policies on individual decisions and, ultimately, on an array of sustainability measures applied to urban regions, including aggregate and disaggregate physical and social variables. Physical variables indicate energy use, pollution emission and carbon sequestration. Social variables include agent utility measures. These variables are used to compute information indexes, discussed in the next section, to determine the stability of the urban system under each policy regime.

In its current version, USAFE includes diverse agents (e.g., residents and farms) making choices about development, location, transportation, and energy consumption. The environment is represented as a two-dimensional lattice of cells containing natural, infrastructure and policy attributes, including forest cover, soil quality, presence of roads, zoning density restrictions and municipal water and sewer coverage. Agents' decisions are affected by their individual preferences for location (e.g., proximity to cities and natural areas, crime rate, the ranking of public school districts and density of development), by policy (e.g., zoning restrictions and infrastructure) and by landscape characteristics (e.g., soil quality and land availability for urban development). Energy consumption and pollution emissions result from operational use and transportation, both dependent on density of development, distance to main destinations, type of fuel and share of energy production, and fuel efficiency. Agents' land-use decisions affect the assimilative capacity of the environment through forest clearing and re-growth, and subsequent urbanization through adjacency effects. Each time step corresponds to one year. The sequence of events for the USAFE model is included in the Appendix.

USAFE is built with the Java RePast[1] simulation platform. The parameter values and mechanisms of the models are based on existing literature and expert knowledge about the various decision-makers and processes that are represented in the model (ultimately, we will use historical data from actual metropolitan areas). Interaction effects between the various components of the model are assessed by sequentially varying the behavioural, policy and biophysical dimensions, and examining their impacts on the simulations outputs.

2.1. Environment

The environment is defined as a two-dimensional lattice composed of square cells of equal size, each cell representing a specific surface area. Both the lattice and the cell surface are defined by a parameter of the model. Associated to this lattice is a series of grid data layers containing natural, infrastructure, social, proximity, and policy information (Table 1).

Empirical evidence and literature suggest that these factors influence farmland conversion and residential location decision-making, referenced in detail in the sections below corresponding to each type of decision. Stochasticity, agent and landscape heterogeneity, and path-dependence will ultimately determine how the landscape is developed.

2.1.1. Land conversion

Cells are created at model initialization and assigned a farm land-use type by default. Alternatively, the assignment of land-use types may be determined by an input map. Farm cells transition to an undeveloped state, after which they become available for subsequent residential development, at a rate defined by a parameter of the model (Fig. 1a). This rate determines the number of randomly selected cells to be evaluated for transition at each time step. If a selected cell has poor agricultural soil and contains a road, it will be converted to undeveloped. If the cell has a road and good agricultural soil, the probability of transitioning is set to be at least 80%, increasing with increasing adjacent development. Otherwise, with good agricultural soil and no roads, the probability that a cell will transition to undeveloped depends only on surrounding development. Once the cell is converted, it is ready to be occupied by residents, according to decision rules that are described in Section 2.3.1.

[1] http://www.repast.sourceforge.net/index.php.

Table 1
Landscape quality spaces in USAFE

Land use
Natural features
Agricultural quality
Septic quality
Forest cover
Infrastructure
Presence of roads
Municipal water coverage
Municipal sewer coverage
Social
Ranking of schools
Crime rate
Proximity
Distance to natural areas
Distance to centre of employment
Policy
Residential-density restriction (zoning)

The farmland transition rates and mechanisms are based on current land-use trends in Southeast Michigan, expert knowledge of farmers' decisions to free up land for residential development (Maniko, personal communication, 2004; Nassauer, personal communication, 2004), and literature studying the role of speculation and of transportation and service infrastructure in encouraging development around existing residential areas (Bogart, 1998; Ewing, 1994, 1997). Nevertheless, current mechanisms and rates in the model may be changed with new empirical information.

2.2. CO_2 assimilation

Low-density development is often more conducive to forest preservation, depending on the type of development, while fewer opportunities for forest cover exist in dense areas. While forest cover enhances assimilation, low density has two opposing effects: it increases the distance travelled and the household electricity use (see Section 2.3.2) while limiting the number of households that consume energy and travel. In this version of the model, forest is assumed to be maturing at a constant rate wherever it is present. This simplifying assumption allows us to explore the advantages and disadvantages of varying urban and suburban densities.

The assimilative capacity of the environment for CO_2 is calculated at each time step by computing the surface of forest cover in the entire lattice and multiplying it by 1,800,000 grams of carbon units absorbed by one hectare of forest per year, divided by 0.27 units of carbon per unit of CO_2 (Rees, 1996). This determines the amount of the gas that can be absorbed by existing forest, which is subtracted from the cumulative emissions from residential electricity and fuel use to determine final global concentrations of the green house gas. If the result is negative, global concentrations are zero.

2.3. Agents

There is one type of agent in this version of USAFE, which has attributes and rules of behaviour corresponding to residents. Residents have different preferences for location, and decide to move to a cell according to how well it matches their preferences. Their choice of location affects their energy consumption and pollution emissions, explained below (Section 2.3.2) (in future versions, the behaviour rules will be modified to reflect location and consumption responses to energy prices, pollution and policies). Farmers are proto-agents, in that they are described by rules of behaviour defined at the cell level and that depend on landscape attributes and adjacency effects; energy consumption and corresponding emission of pollutants are of an undefined type in this model version and are constant for all farm cells. The decision to represent behaviour in agent or in cellular form was determined by the level of detail and heterogeneity in the land-use and energy-use processes at this stage of development of USAFE. This will be restructured into agent-based form when more information is gathered about farm decision-making.

2.3.1. Location decisions

Residents enter the environment at a predetermined rate (1000 per time step in this version) and choose to locate on undeveloped cells using a hedonic utility calculation that is partly based on survey data (University of Michigan, 2001) and on literature (Downs, 1994; Ehrenhalt, 2000; Ewing, 1994; Garreau, 1991; Gordon & Richardson, 2000; Heilbrun, 1987; Henderson & Moore, 1998;

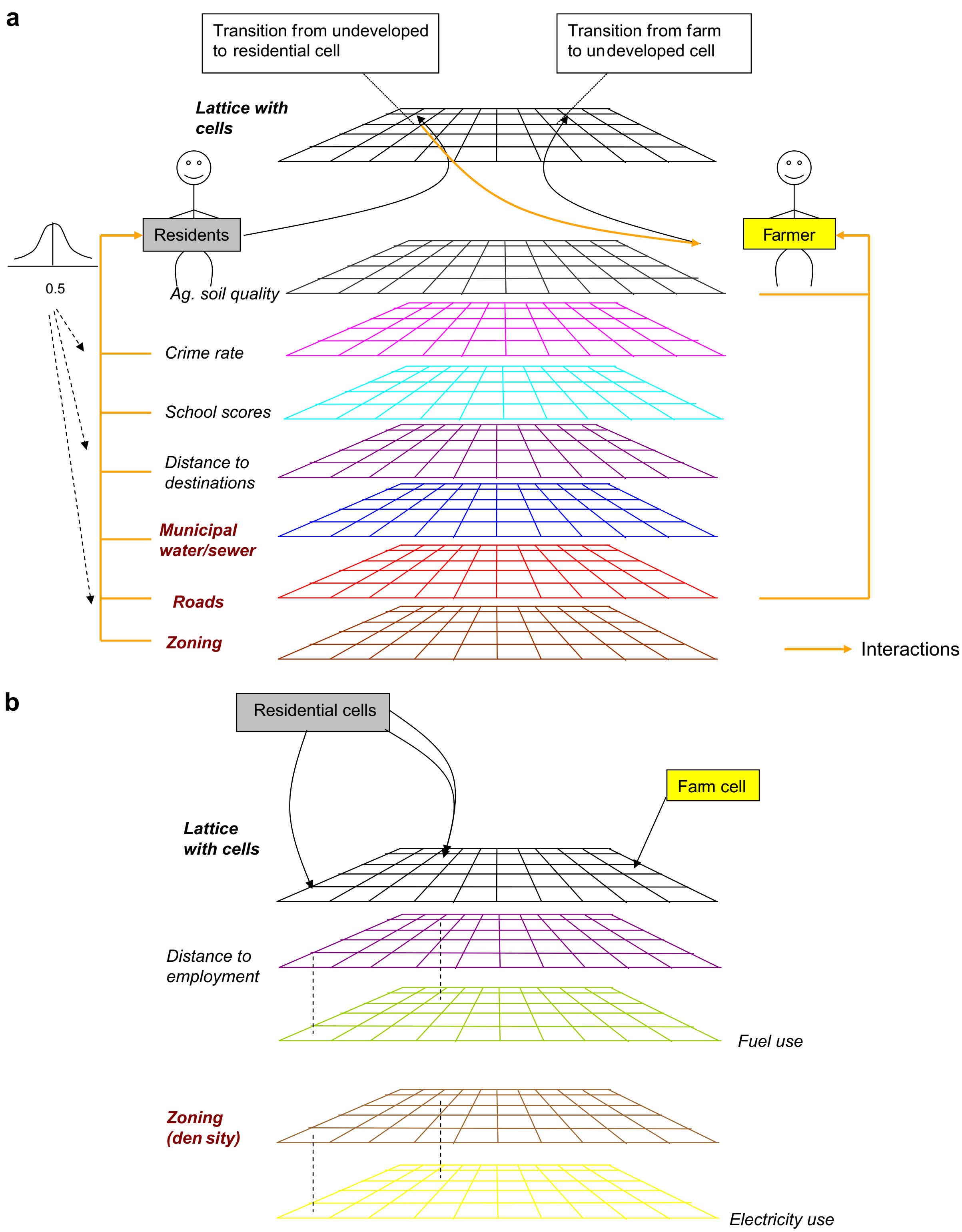

Fig. 1. USAFE: (a) land-use decision-making mechanisms; (b) energy consumption mechanisms; (c) air pollution emissions.

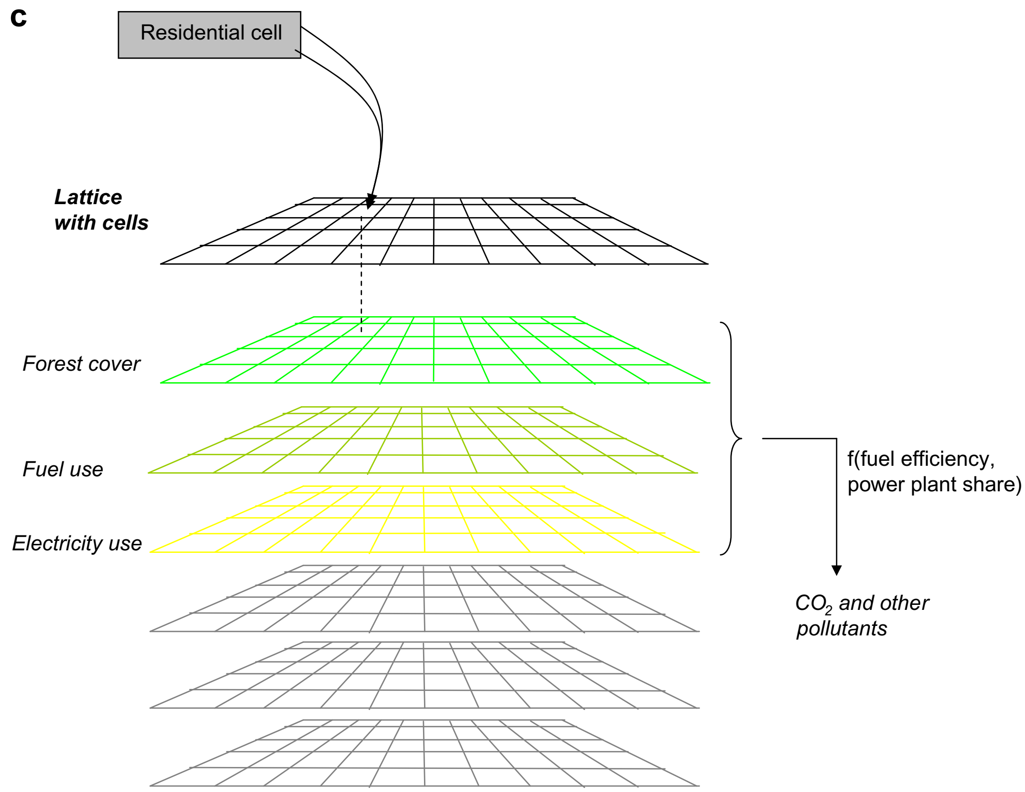

Fig. 1 (*continued*)

Hirsch, 1984; McKee & McKee, 2001), and that accounts for convenience of access, crime levels, quality of public schools, proximity to major employment centres and natural areas, and density of surrounding development (Fig. 1a). Based on the survey data, proximity to work and natural areas and convenience of access are two dimensions that affect accessibility. They are therefore represented as two kinds of landscape variables for which residents have preference: (1) distance (a continuous variable), and (2) presence of a road (a binary variable). Residential preferences are assigned for new agents when they are created at each time step. Population preference values follow a normal distribution around a mean value that is set as a parameter of the model for each factor of preference, and with a fixed standard deviation of 0.02. Although the standard deviation could be changed, it has been shown that the existence of variability matters more than the size of such variability (Brown & Robinson, 2006; Rand et al., 2002). All residents are also set to value municipal provision of water and sewer, and in cases where there is no sewerage they prefer to locate on septic soils.

Residents decide their location by evaluating a random set of cells available for residential occupation, representing the bounded knowledge they may have of the real estate market through realtors. The number of cells that enter the sample is determined by a parameter of the model. Residents evaluate each cell according to a utility function of the following form, where all factors are normalized between 0 and 1:

$$U = \alpha_r r + \alpha_e(1-e) + \alpha_n(1-n) + \alpha_k k + \alpha_c(1-c) + \alpha_z(1-z) + \alpha_w w + \alpha_s s, \tag{1}$$

where

α_r = residential preference for proximity to road;
r = cell presence of road (binary);
α_e = residential preference for distance to employment;
e = cell distance to employment;
α_n = residential preference for distance to natural area;
n = cell distance to natural area;
α_k = residential preference for good schools;
k = cell school scores;
α_c = residential preference for low crime;
c = cell crime levels;
α_z = residential preference for low density;
z = residential density permitted by zoning;
α_w = residential preference for municipal water coverage;
w = cell presence of municipal water (binary);
α_s = residential preference for either sewer coverage or septic soil;
s = cell presence of either sewer coverage or septic soil (binary).

Each resident locates on the first cell from the random set from which they derive the highest utility. If the selected cell has reached the maximum density permitted by zoning, it is withdrawn from the pool of available cells and no further residents can move in. Otherwise, the cell remains available for future residents. The pattern in which residents settle emerges from the combination of residential preferences, zoning and adjacency effects of development on farm cells.

2.3.2. Energy use and air pollution emission

Household electricity use and transportation fuel consumption are fundamentally different processes with unique efficiency and pollution rates, and they are separate in the model (Fig. 1b). Household electricity consumption rates decrease with increasing permitted density, assuming that houses are smaller in dense areas. The model has two parameters governing this density-dependent energy use indicating minimum (555 kW h) and maximum (1332 kW h) electricity usage per household, based on existing information of average monthly residential electricity use in different states across the US (Department of Energy, 2005). Although reasonable, these default values may be changed to reflect different energy usage scenarios. Each household is then assigned a level of consumption that depends on the maximum possible density permitted in each cell, as determined by

$$E_{h,c} = (1 - z_c)(E_{\max} - E_{\min}) + E_{\min}, \tag{2}$$

where $E_{h,c}$ = monthly electricity use in household h located in cell c; z_c = residential density permitted by zoning in cell c; $E_{\max}$ = maximum household electricity use; $E_{\min}$ = minimum household electricity use.

During each time step of the simulation, $E_{h,c}$ is multiplied by the number of households in each cell and the 12 months in a year to collect the information of annual electricity use in each cell:

$$E_c = E_{h,c} \times r_c \times 12, \tag{3}$$

where E_c = annual household electricity use in cell c; r_c = number of residential households (agents) in cell c.

Transportation energy use in the model rises with increasing distance to employment centres, and total fuel consumption in each cell is determined by this distance and the fuel efficiency of private vehicles, another parameter of the model. The default value for this parameter is 30 miles per gallon. Fuel consumption increases with the number of commutes per week, another model parameter whose default value is five round-trips, and by 52 weeks in a year:

$$F_c = \frac{d_c}{f} \times r_c \times m \times 52 \times 2, \tag{4}$$

where F_c = annual fuel use for transportation in cell c; d_c = distance from cell c to central business district; f = fuel efficiency; m = commuting round-trips per week (m = 5 in default scenario).

Emissions of air pollutants are a function of the share of utility plants powered by different fuels, of household electricity use, and fuel used for transportation and farm operations (Fig. 1c). Utility plants considered include those powered by natural gas, coal, oil and municipal waste. Nuclear power plants were excluded, since their production of air pollution is negligible. These plants produce different levels of CO_2, SO_2 and NO_x. USAFE computes emissions of each gas by multiplying the rate of pollution emission per unit of electricity generated (g/kW h), based on accepted emission factors (US Environmental Protection Agency, 2006), by the electricity consumed by households in each cell, as defined above, and by the share of power plants of each type. The model also estimates the amount of VOC, CO, NO_x, PM, SO_x, CH_4, N_2O and CO_2 generated by residential transportation originated in each cell. The amounts are computed by multiplying the total use of fuel for transportation times the corresponding emission factors in grams for each contaminant per gallon of fuel. We took the emission factors for conventional gasoline vehicles from the Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation model (GREET) developed by Argonne National Laboratory. The computation of emissions for each pollutant combines both sources—electricity use and transportation—as follows:

$$P_{x,c} = F_c \times t_x + a(E_c(s_g \times p_{x,g} + s_k \times p_{x,k} + s_o \times p_{x,o} + s_w \times p_{x,w})), \tag{5}$$

where

$P_{x,c}$ = annual emissions for pollutant x originated in cell c;
t_x = emission factor for pollutant x from transportation;
a = binary variable that takes the value of 1 when pollutant x is produced by power plants;
s_g = share of power plants operating with natural gas;
$p_{x,g}$ = emission factor for pollutant x from natural gas power plants;
s_k = share of power plants operating with coal;
$p_{x,k}$ = emission factor for pollutant x from coal power plants;
s_o = share of power plants operating with oil;
$p_{x,o}$ = emission factor for pollutant x from oil power plants;
s_w = share of power plants operating with municipal waste;
$p_{x,w}$ = emission factor for pollutant x from municipal waste power plants.

2.4. Spatial and aggregate outputs

USAFE produces a variety of spatial and temporal outputs. The model stores land use (the number of agents if it is residential), fuel and electricity use and pollution emission in each cell, reproducing the distribution in a two-dimensional lattice at the end of each run. Using GIS, spatial analyses can be conducted on the collection of matrices providing information about averages and distributions, as well as spatial correlations. In addition, USAFE produces a report at the end of each run with global values of pollution emissions for each air pollutant and for forest cover. Global emissions are calculated and reported for each time step combining both residential sources of pollution. We test the effect of behavioural, physical and policy variables on these outputs by changing the parameter values of the USAFE model (Table 2).

Agricultural energy use and emissions are kept separate from residential activity. We focus on farm operation only, and do not attempt to include the production of inputs or transportation of outputs for agricultural activity. A parameter in the model determines the rate at which each farm cell uses energy and a second parameter determines the amount of pollution generated by each unit of energy used. More detail will be added to the model as we collect further information on agricultural activity.

Table 2
Parameters and default values in USAFE

Parameter (units)	Default value
Run time	200 time steps
Size of grid	200 by 166
Initial land-use	All farms
Forest cover	0 in all cells
Roads	In all cells
Municipal water and sewer	In all cells
Zoning	311 residents/cell
Agricultural soil quality	Poor in all cells
Central business district	Centre of lattice
Natural areas	In all cells
School scores	0 in all cells
Crime	0 in all cells
Residents per turn	1000
Transition rate to undeveloped	100
Round-trips per week	5
Residential preference for all factors	0.5
Surface of each cell	63,000.78 m2 (~16 acres)
Maximum electricity use	1332.0
Minimum electricity use	555.0
Share of power generation (natural gas, coal, oil, municipal waste)	0.25 each
CO_2, SO_2 and NO_x from natural gas (g/kW h)	514.82, 0.05, 0.77
CO_2, SO_2 and NO_x from coal (g/kW h)	1020.12, 5.9, 2.72
CO_2, SO_2 and NO_x from oil (g/kW h)	758.4, 5.44, 1.81
CO_2, SO_2 and NO_x from municipal waste (g/kW h)	1355.33, 0.36, 2.45
Farm consumption (undefined units)	100
Farm Pollution Coefficient (undefined units)	1.0
Fuel efficiency (mi/gal)	30.0
VOC from fuel use for transportation (g/gal)	4.637
CO from fuel use for transportation (g/gal)	123.581
NO_x from fuel use for transportation (g/gal)	6.160
PM from fuel use for transportation (g/gal)	0.739
SO_x from fuel use for transportation (g/gal)	1.898
CH_4 from fuel use for transportation (g/gal)	1.882
N_2O from fuel use for transportation (g/gal)	0.627
CO_2 from fuel use for transportation (g/gal)	8744.611

2.5. The Fisher Information Index

We use the reports generated by USAFE to calculate the Fisher Information Index for each scenario. Fisher information was initially formulated as the information obtainable from a set of measurements or observations on a variable s in an effort to estimate a value for an unobservable parameter θ (Fisher, 1925). Recent work has derived many well-known physical and biological laws from Fisher information (Frieden, 2004). Starting from these results, Cabezas and colleagues have developed the Fisher Information Index as a means of defining the stability, degree of order, and sustainability of a variety of systems, including ecological, industrial, economic, social, and governmental (Cabezas, Pawlowski, Mayer, & Hoagland, 2003, 2005; Fath, Cabezas, & Pawlowski, 2003; Mayer, Pawlowski, & Cabezas, 2006; Mayer, Thurston, & Pawlowski, 2004; Pawlowski, Fath, Mayer, & Cabezas, 2005). The general logic of the index is as follows: (1) Fisher information is a measure of information obtainable from observations, (2) information can be obtained from data only if there are patterns present in the data, i.e., no useful information can be obtained from truly random data, (3) the existence of patterns implies that there is order in the data (random data has no order

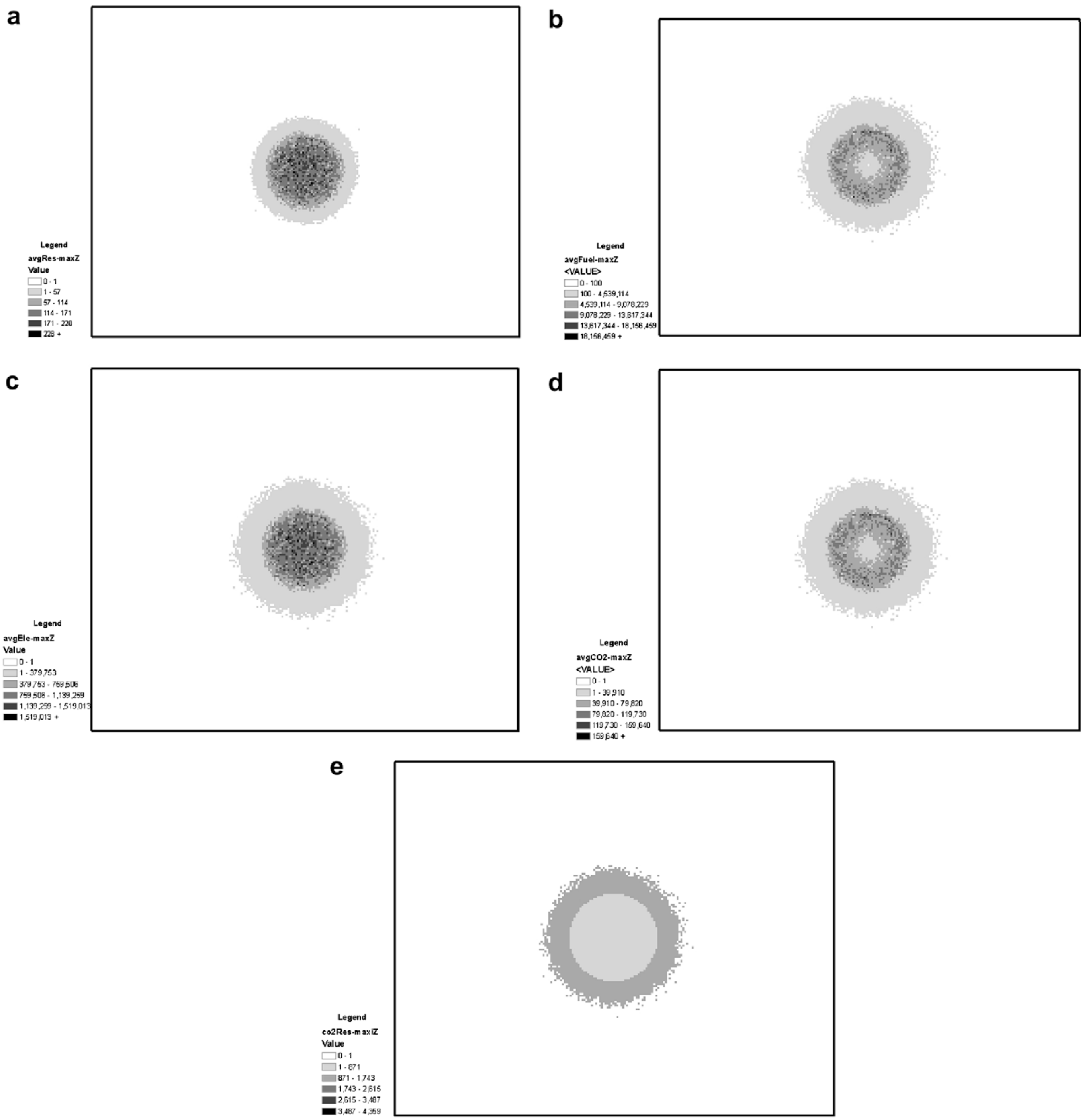

Fig. 2. Spatial outputs of default scenario, averaged for all runs: (a) density (residents/cell); (b) fuel use (gal/cell); (c) electricity use (kW h/cell); (d) CO_2 emissions (Tn/cell); (e) CO_2 emissions (Tn/resident). *Note*: darker shades show higher values.

or useful information), and (4) Fisher information must, consequently, be a measure of order. This is important because many well-functioning dynamic systems have order which is typically lost as the system undergoes a regime change (defined as a transition that changes the structure and functioning of the system as a result of one or more independent factors) or simply begins to malfunction. For the case of complex systems, no two dynamic regimes normally have the same degree of order or the same Fisher information, i.e., each regime has its own set of distinct patterns. Hence, when a system shifts from one dynamic regime to another, the transition is often seen as a temporary loss of order and a sharp drop in the Fisher information. The results for this application of Fisher information show remarkable consistency across different systems and explain many system-wide dynamic regime shifts. The Fisher Information Index is therefore a promising means from which to derive trends that describe the current regime of a system, and in some cases anticipate its future condition. Since Fisher information can operate on different types of data (e.g., physical, technical and social) it offers the ability to integrate across social, economic, and material and energy flow regimes.

The actual mathematical procedure for computing the Fisher Information Index from time series data is well documented elsewhere (Karunanithi, Cabezas, Frieden, & Pawlowski, 2008; Pawlowski et al., 2005). We outline it here for continuity and clarity. A trajectory of the system over time can be defined by plotting the values of its observable variables, e.g., carbon emissions, at each time step in a phase space define by the variables and time. There is an inherent uncertainty in the measurement of any variable including emissions so that any two points in the trajectory that differ from each other by less than this measurement uncertainty are indistinguishable, and they can therefore be considered to be the same value repeated over time. In this manner, all the points in the trajectory can be grouped into different sets, defined as states of the system. The system trajectory—the series of points—is then converted to a sequence of states ordered in time. Note that one can also construct states relative to a base case or reference system or a regime of systems rather than measurement uncertainty. The probability of observing a given state of the system is then assumed to be proportional to the number of points inside that state. This allows us to build a probability function giving the likelihood of observing states of the system. We connect these developments to Fisher information through the shift invariant form of the Fisher information, as follows:

$$I = \int \frac{1}{p(s)} \left[\frac{\mathrm{d}p(s)}{\mathrm{d}s}\right]^2 \mathrm{d}s, \tag{6}$$

where I = the Fisher information, $p(s)$ = probability density for state of the system s, s = a state of the system.

Note that I depends on $p(s)$ and the slope of $p(s)$ with respect to s. For a system in perfect order, i.e., one that never changes, the measurable variables always have the same value, the system is always in one state, and then the probability of observing the favored state is one. Here, $p(s)$ is very sharp, the slope $\mathrm{d}p(s)/\mathrm{d}s$ approaches infinity, and the Fisher information approaches infinity as well. That is, a great deal of information can be obtained from a system that has very well fixed and rigid patterns. On the contrary, for a system in perfect disorder that constantly changes in a completely random and uncorrelated manner, the probability of observing any particular state is small and equal to the probability of observing any other state. Then $p(s)$ is small and very broad or even flat, the slope $\mathrm{d}p(s)/\mathrm{d}s$ approaches zero, and the Fisher information approaches zero as well.

Because systems in stable regimes show characteristic order and order is lost as a regime change occurs, we are able to assess the possible impacts of specific policies and behavioural changes on the future sustainability and dynamic regime of the urban system in terms of Fisher information computed from electricity use, fuel use, and CO_2 emissions produced by the agent-based model—future work will involve analyzing other pollutants and natural and socio-economic variables over time and space. The code to compute the Fisher Information Index was programmed in MATLAB. The electricity use, fuel use, and CO_2 emissions time series data generated by the agent-based model for various scenarios were fed into the Fisher Information Index code as input data and the time-averaged Fisher information values were calculated for each of the scenarios by (1) dividing the time series data points for a given scenario into a sequence of time windows (each time series data point is a vector with three coordinates—one for each output variable—plus time, forming a four-dimensional phase space); (2) distributing the time series data points into the time windows in the phase space trajectory; (3) dividing the four-dimensional phase space within each time window into multiple system states where the sides of each state are equal to four standard deviations computed from the variation of each variable for the default or base case scenario (described in Section 3); (4) distributing the phase space data points into the system states until all the points within the given time window are accounted for; (5) constructing the probability density function (pdf) for observing a given state within the given time window by counting the number of points inside each state. Once the pdf has been constructed, the time-averaged Fisher information for the given time window is then computed using Eq. (6). After calculating the Fisher information for a given time window, the time window is moved by a specified number of time steps such that there is an overlap, and then the average Fisher information is computed over the new time bracket. The Fisher Information Index for all the time windows is calculated as above and these values are plotted as a function of time.

3. Scenario simulations and results

The scenarios suggested are highly stylized for the purposes of illustrating the applicability of this integrated framework to urban policy assessments. Here we focus on assessing the extent to which a suite of urban policies influence location

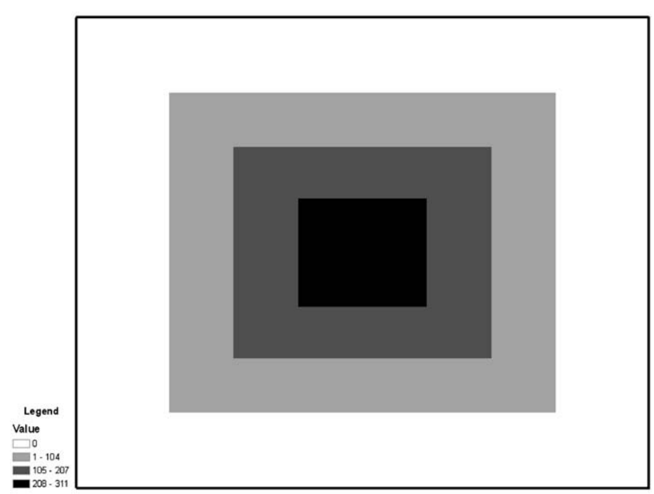

Fig. 3. Spatial layout of concentric scenarios. *Note*: darker shades show higher values, in this case, for concentric zoning; good central schools show a similar distribution for values between 25 and 100, while good peripheral schools show the inverse distribution.

decisions, in turn shaping urban form and density of development and, consequently, affecting air quality. In particular, we examine how spatial variations in zoning restrictions and school examination scores—assumed to depend on school spending—may cause different levels and distribution of consumption and pollution. We also examine the effect of changes in commuting behaviour, and compare the resulting consumption and emissions with those obtained in the policy scenarios. Other possible scenarios and improvements to the USAFE model are discussed in Section 5.

3.1. The default case

Table 2 shows the parameter values for the default case. In the variables of concern, maximum density (311 residents per cell) is allowed and scores for all schools (i.e., the percentage of students

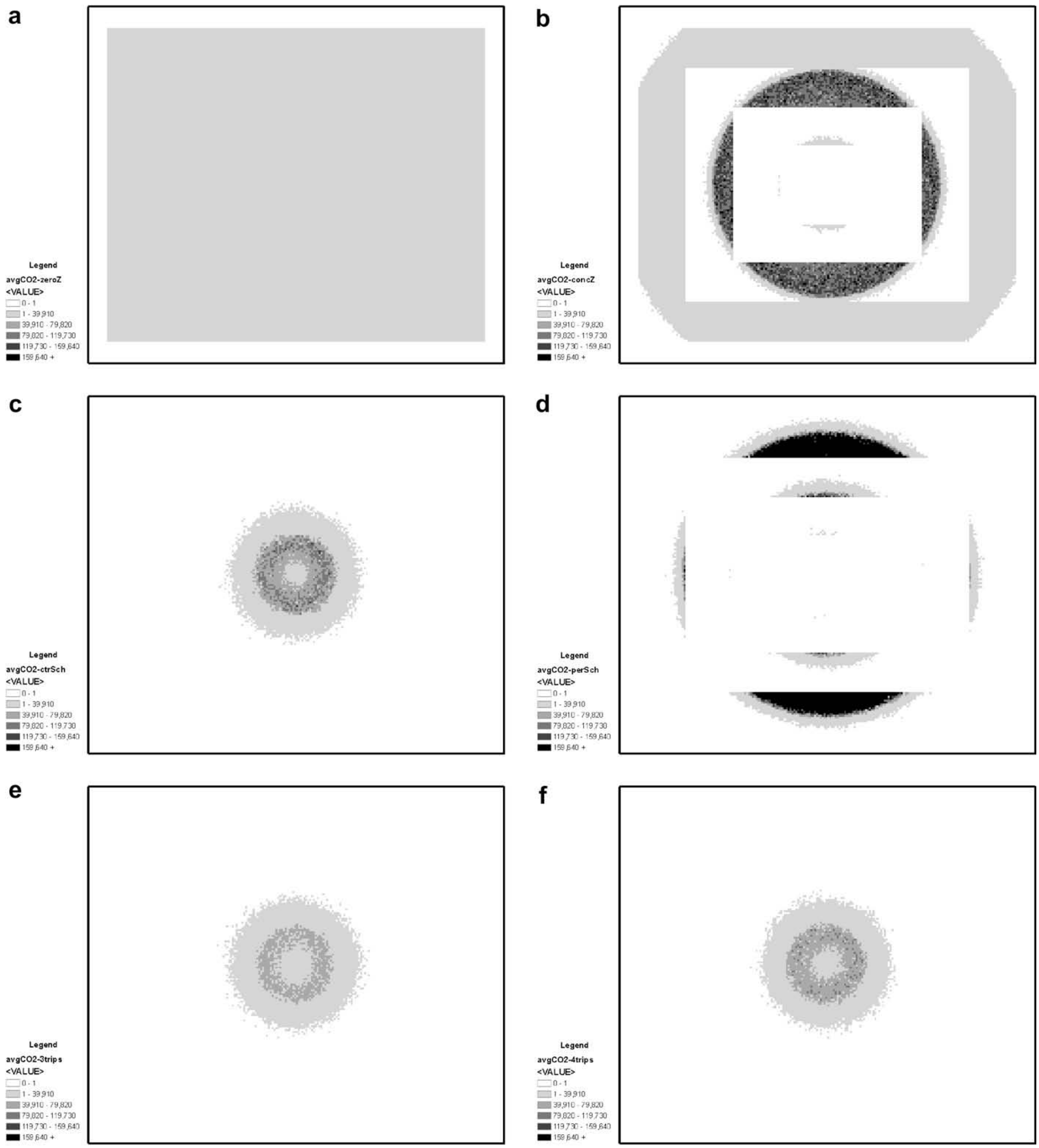

Fig. 4. CO_2 emissions for all scenarios (Tn/cell), averaged for all runs: (a) minimum density zoning; (b) concentric zoning; (c) good central schools; (d) good peripheral schools; (e) three trips per week; (f) four trips per week. *Note*: darker shades show higher values.

passing standard exams) are zero in all cells of the hypothetical area, so that residential location is not influenced by these factors, and each residential household commutes five times a week.

Fig. 2 shows the spatial outputs produced by USAFE, as an average of all 20 runs for this scenario. Without zoning restrictions and as a result of the decisions in this model, all residents tend to locate around the central business district. Densities are high around this centre, reflected in the higher use of electricity that decreases outwards. Commuting distances are very short immediately surrounding the centre, so that CO_2 emissions are low. Increasing distance induces more fuel use and emissions, but these decrease again towards the edges of urbanization as new development occurs. This pattern reverses when measuring the emission levels per capita. The fewer residents in the outskirts actually contribute with proportionally higher emissions, given their longer commuting distances.

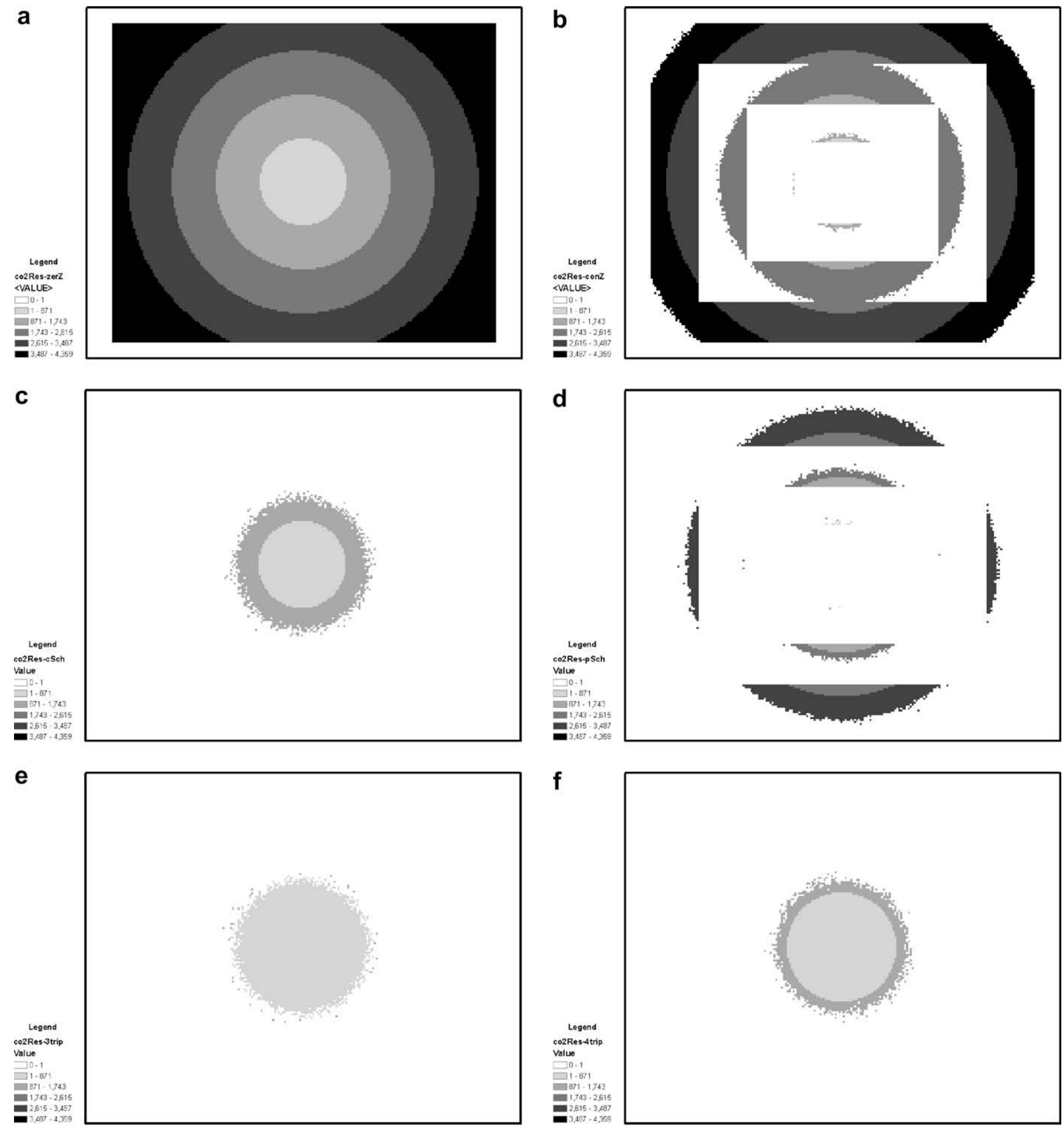

Fig. 5. CO_2 emissions for all scenarios (Tn/resident), averaged for all runs: (a) minimum density zoning; (b) concentric zoning; (c) good central schools; (d) good peripheral schools; (e) three trips per week; (f) four trips per week. *Note*: darker shades show higher values.

3.2. Spatial outputs for alternative scenarios

The alternative scenarios vary the spatial layout of zoning, which ranges from uniform restrictions allowing only one residential agent per cell (minimum zoning) or 311 per cell (maximum zoning), to a concentric layout that allows maximum density near the central business district, with decreasing densities towards the periphery (concentric zoning, see Fig. 3). The concentric zoning scenario was chosen based on trends of monocentric development, where high densities of development are typically permitted at the centre of an urban area, with decreasing densities towards the periphery. Zoning usually follows this pattern, as higher densities are usually tolerated and in some cases actively supported in central districts, and resisted in suburban areas.

The same concentric pattern was used to generate the spatial layout of school scores. Two alternative scenarios were considered, one where schools of better quality are located at the centre (good central schools), and an inverse distribution, where peripheral public schools are better than those located in the inner city. These scenarios are meant to reflect current trends in divestment in inner city schools, and an alternative policy. Given the influence of school quality on residential location (e.g., University of Michigan, 2001), such policies could significantly affect energy use and pollution emissions.

Finally, we consider scenarios in which the commutes to work are reduced, relative to the default scenario. With the development of information technology, weekly trips could be eliminated. Our intent was to examine the degree to which such behavioural change could address the environmental concerns covered here, and if it should therefore be actively promoted by policy-makers.

Figs. 4 and 5 compare the spatial output for CO_2 emissions per cell and per resident, respectively, for the alternative scenarios. Table 3 gives a complementary perspective on these outputs, as it aggregates the results over the entire lattice.

In the case of minimum zoning, total emissions and emissions per unit area are very low. This is because only one resident is allowed in each cell, greatly limiting the total number of residents that can move into the lattice, and thus the fuel and electricity that is consumed. However, if we look at the both the spatial and the aggregate values for emissions per household, this is the scenario that produces the highest values.

Both the concentric zoning and the good peripheral schools scenarios produce a pattern that tends to disperse urbanization towards the edges of the lattice. In the first case, this is because residents now have a choice of density as there are different zoning restrictions and most of them prefer medium densities, located away from the city centre. As residents locate in lower densities, they fill up cells faster, encouraging more spreading out and longer commutes. The difference with the good peripheral schools is that all residents prefer them and most of them will then locate in the edges of their districts closer to the city centre.

Table 3
Aggregate values for electricity use, fuel use and CO_2 emissions

Scenario	Residents	Electricity (kW h)	Fuel (gal)	CO_2 (Tn)	CO_2/res (Tn/res)
Default scenario	*199000.0*	*1.33E+09*	*1.23E+10*	*1.09E+08*	*5.45E+02*
Minimum density zoning	19900.0	3.18E+08	6.08E+09	5.34E+07	2.68E+03
Concentric zoning	199000.0	2.58E+09	4.76E+10	4.19E+08	2.10E+03
Good central schools	199000.0	1.33E+09	1.22E+10	1.08E+08	5.41E+02
Good peripheral schools	199000.0	1.33E+09	5.92E+10	5.19E+08	2.61E+03
Three round-trips/week	199000.0	1.33E+09	7.29E+09	6.49E+07	3.26E+02
Four round-trips/week	199000.0	1.33E+09	9.74E+09	8.64E+07	4.34E+02

The unique spatial pattern of these two scenarios results from the combination of grid size, population (determined by the length of the run), residential preferences, and the spatial layout of zoning restrictions or school scores. The construction of new schools in urban peripheries and the fixed residential-density restrictions in these areas encourage leapfrogging and discontinuous patterns of development. This is why these scenarios are the second and third more polluting.

Another set of scenarios corresponds to good central schools and reduced trips to work. These are also similar to the default case, in which development occurs close to the city centre. In the case where good schools are located around the city, it reinforces the trend towards compact development. When trips are reduced, we observed the expected reduction in fuel use and emissions, particularly in terms of emissions per capita (given the mechanisms in the model, only if there are different zoning restrictions will there be a difference in electricity use).

3.3. Fisher information for alternative scenarios

The results of the Fisher information (FI) analysis suggest there are significant differences in the dynamic order of some scenarios (Fig. 6). Moreover, scenarios can be grouped according to their impact on the sustainability of the system. In one extreme, the scenarios with minimum density zoning and fewer round-trips per week result in highly ordered systems, with consistently high values of FI. An explanation for this is that in the first scenario, the number of residents is greatly limited, resulting in a population ten times smaller than in other scenarios. With a low population, the scenario has low environmental stress, and is quite static with respect to consumption and system interactions. The lack of activity in the minimum density zoning scenario manifests in a system with high FI, and therefore a stable and highly ordered system. Although the spatial pattern of development is different when commuting trips are reduced, the overall emissions are also restricted; thus the similarity among these scenarios.

In the other extreme, the scenarios with concentric zoning and good peripheral school produce consistently low FI values over time, indicating that the system has low dynamic order. This is not too surprising, since these scenarios produce the most dispersed urbanization patterns, encouraging long commutes and lower densities of development.

The default and the good central school scenarios show medium values for FI because they produce compact spatial patterns but, in contrast with the reduced trips scenarios, they generate more emissions. Because of the central location of urbanization, however, these scenarios generate more orderly systems than in the concentric zoning and the peripheral good schools scenarios (i.e., higher FI values). Because residents are attracted to good schools and employment, when these are in the same locations less fuel is consumed and less CO_2 emissions are generated. Thus, the reduced volatility in the system is reflected in higher stability and dynamic order than in the peripheral schools scenario.

A comparison of the number of automobile trips taken during a week produced very interesting results. The three round-trips per week scenario manifests high and constant FI, and therefore indicates a highly ordered and stable system. Once the number of automobile trips per week reaches four, the system undergoes a systemic transition in which the FI begins to oscillate in a dramatic fashion. This would indicate a system that is very close to a regime change, and which is fluctuating between two alternative dynamic regimes having high and low Fisher information, respectively. Note that then in the default scenario, with five automobile trips per week, the system exhibits low FI with minor

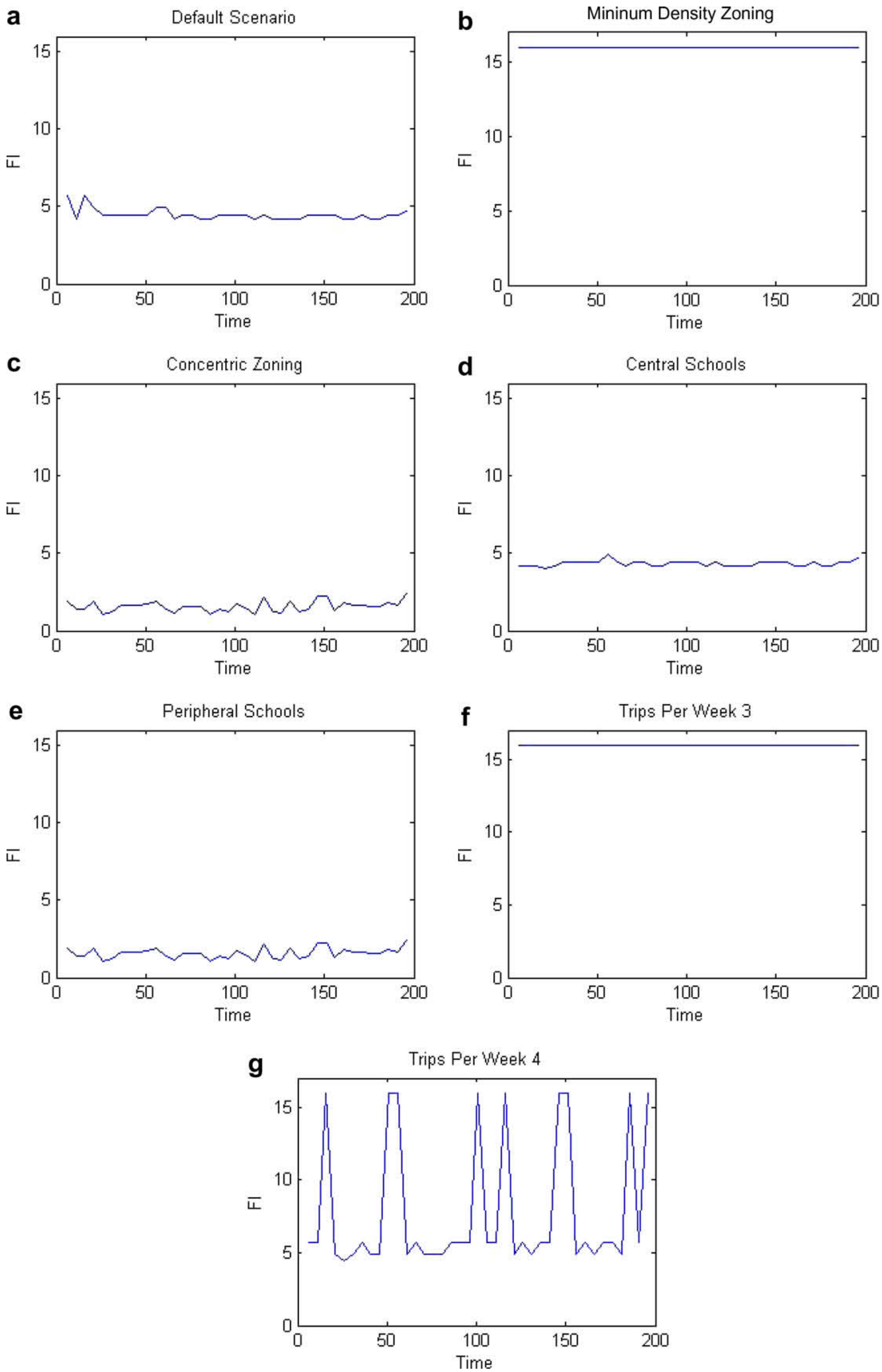

Fig. 6. Fisher index for different scenarios: (a) default; (b) minimum density zoning; (c) concentric zoning; (d) good central schools; (e) good peripheral schools; (f) three trips per week; (g) four trips per week.

oscillations, which indicates that the system has lost dynamic order but it is stable. While finding a simulation precisely at the point between two alternative dynamic regimes may have been fortuitous, the interpretation of the observed results seems to be robust because it follows the logic of the underlying theory. With more automobile trips, there is more fuel consumption and therefore more CO_2 emissions. This transition from three to four to five automobile trips per week manifests in a dramatic shift from a highly ordered system to an oscillating period of transition and a shift to a less orderly system. This is what one would expect for a system that has gone through a regime change.

4. Theoretical and policy implications

The use of agent-based models allows us to increase our understanding of how the interaction among different factors (e.g., individual preferences, landscape characteristics, fuels, technology, policy) are expressed differently in spatial and temporal patterns, depending on socio-economic, institutional and environmental circumstances. The results from Fisher information for the time series data offer additional insights relative to the desirability of future urban scenarios according to their order and stability.

These preliminary explorations allow us to examine how small changes in behaviour, land-use policies and investment in public schools may have significant impacts on environmental quality and long-term sustainability. Land use and education policies could become environmental policies, perhaps more so than technological regulations. The mechanisms relating sprawl and school development has only recently gained more attention (e.g., Norton, 2007), and promises to attract further research. Still, the effectiveness of one versus the other remains to be studied. Another role for technology, however, is in the possibility of telecommuting and reducing actual trips to work; just eliminating one trip per week would greatly reduce both fuel consumption and pollution and stabilize the entire system, likely at a much lower cost than enforcing technological changes in vehicles for similar impacts. Policy-makers, therefore, could engage in promotion and information activities, particularly with employers, so that this behavioural change is allowed.

Finally, the results from the minimum density zoning scenario suggest that air quality improves with lower densities, also enhancing the sustainability of the system. This is true if we only consider global measures of emissions. If we consider emissions per capita, the conclusion is the opposite. This suggests that, in a complex world with scarce resources, policy analysis should be carried out using a suite of measures to more effectively guide decisions. USAFE can facilitate such analysis.

The relationship between urban form and environmental quality is not simple and varies with the scale of analysis. Combining agent-based modelling and information indexes can help scholars and policy-makers evaluate the common theoretical and practical assumptions about the sustainability, efficiency and equity of specific urban decisions, land-use patterns and their effects on energy use and air quality. This framework can be expanded to include newer information of the mechanisms currently represented, other environmental resources, such as water supply and quality, and other policy instruments, such as crime prevention, infrastructure investments and market-based instruments. In any case, the complexity of urban systems requires the review and adjustment of policy decisions on an ongoing basis. The proposed framework facilitates policy adaptation as more knowledge is produced through the assessment and as conditions of the metropolitan system changes.

5. Future work

Before it can effectively be used for policy, the proposed framework requires further testing and fine-tuning, creating scenarios with the factors currently present in USAFE but that have not been tested for this paper. Tests will explore the influence of alternative zoning and school improvement layouts, crime reduction, infrastructure decisions (e.g., road construction, water and sewer coverage) and forestation. Technological scenarios will test the effect of different sources of power generation, fuel efficiency and emission factors. We will analyze the effect of urban patterns on the other pollutants included in the model but not tested here, and use the Fisher Information Index applied in both time and space to assess the sustainability of the different urban scenarios.

We also seek to apply this framework to specific case studies, for which we will collect spatial data to adjust USAFE's input maps and parameter values. In this effort, we will also adjust farm decisions to reflect more realistic fuel use and resulting emissions.

An initial extension to the model is planned to show forest clearing and re-growth. Development is both attracted to forested areas and is the cause of forest clearing. Such forces make it difficult to anticipate the effectiveness of forest protection policies, for example, on carbon assimilation. A second extension of the model will link crime to population characteristics. Both crime and residential density increase with development pressures, and also discourage further development. Currently, forest cover, zoning restrictions and crime rates are fixed as initial conditions. By allowing them to vary with development, USAFE will enable us to explore the path-dependence typical of urbanization processes that are only weakly represented in the current version of USAFE. A final extension of the model will compute the utility of residents to determine the distributional effects of policies, accounting for private and public gains (e.g., location amenities, carbon sequestration) and private and public losses (e.g., transportation costs, pollution). We expect that the Fisher Index will be especially powerful in assessing the outputs in these scenarios.

As much as improvement is necessary, increasing the detail and complexity in the model will be at the expense of understanding. This is an inherent challenge of using complexity-based modelling for policy, extensively discussed in the literature (Bankes, 1993, 2002; Bankes, Lempert, & Popper, 2002; Clarke, 2005; Manson, 2007; Miller & Page, 2007; O'Sullivan & Torrens, 2001). Too much detail leads to excessive complication and comprehensiveness, resulting in "black boxes" whose assumptions and implications are hard to understand and question (Lee, 1973). Too little detail, on the other hand, can also fail to capture the important aspects of the system we seek to understand and propose policies for. Determining the right balance between realism and interpretability in any modelling endeavour is an art, a creative process that requires continuous exploration, experimentation and adjustment within the specific context in which the model is being developed. Through this process, we seek to provide powerful insights about the interactions that shape urban areas, and how they translate not only into environmental quality but also into the stability and sustainability of the urban system over time.

Acknowledgments

The authors are grateful to Susan Zielinski, University of Michigan, and David Berdish, Ford Motors Co., for their contribution to scenario development. We appreciate the insightful comments and feedback of two anonymous reviewers.

Appendix A

Sequence of events for USAFE

1. Initialization
    - Create 2-D grid
    - Create quality spaces (raster-based inputs and outputs)
        - agricultural and septic soil quality
        - forest cover
        - presence of roads
        - municipal water and sewerage coverage
        - ranking of schools
        - crime rate
        - distance to destinations and amenities
        - zoning
        - energy consumption
        - emissions for pollutants of different types
    - Create cells, locate in grid and assign model parameters

2. Iterations
    - Cells transition from agricultural to undeveloped
        - choose farm cells at random
        - if road present
            - if poor soil quality
                - transition
            - if good soil but adjacent development
                - transition with high probability
        - if no road
            - transition with probability proportional to adjacent development
        - if transitioning, convert cells to undeveloped, ready to be occupied by residents
    - Create resident agents
        - create residents in amount determined by parameter
        - assign location preferences according to parameters
        - choose location
            - draw a random sample from list of available cells (undeveloped, residential)
            - evaluate each cell in the sample
                - get scores for each dimension of preference from quality spaces
                - apply equation (1) to determine utility
                - select location with highest utility (best cell)
            - locate in best cell
            - if maximum allowed density is reached, eliminate cell from list of available cells
    - Cells estimate energy use, pollution emission and assimilation
        - determine consumption and pollution according to land use (equations 2 through 5)
        - store values in corresponding quality spaces
    - Model computes global pollution

3. Repeat 2. until t = 200.

References

Affuma, J. K., Browna, A. L., & Chanb, Y. C. (2003). Integrating air pollution modelling with scenario testing in road transport planning: The TRAEMS approach. *The Science of the Total Environment, 312*, 1–14.

Alberti, M. (1999). Urban patterns and environmental performance: What do we know? *Journal of Planning Education and Research, 19*, 151–163.

Bankes, S. C. (1993). Exploratory modeling for policy analysis. *Operations Research, 41*(3), 435–449.

Bankes, S. C. (2002). Tools and techniques for developing policies for complex and uncertain systems. *Proceedings of the National Academy of Science, 99*(3), 7263–7266.

Bankes, S. C., Lempert, R., & Popper, S. (2002). Making computational social science effective: Epistemology, methodology, and technology. *Social Science Computer Review, 20*(4), 377–388.

Bogart, William Thomas (1998). *The economics of cities and suburbs* (1st. ed.). Prentice-Hall.

Brown, D. G., & Robinson, D. T. (2006). Effects of heterogeneity in residential preferences on an agent-based model of urban sprawl. *Ecology and Society: Special Feature on Empirical based agent-based modeling* 11 (1): <www.ecologyandsociety.org/vol11/iss1/art46>.

Cabezas, H., Pawlowski, C., Mayer, A., & Hoagland, N. (2005). Sustainable systems theory: Ecological and other aspects. *Journal of Cleaner Production, 13*(5), 455–467.

Cabezas, H., Pawlowski, C., Mayer, M., & Hoagland, N. (2003). Sustainability: Ecological, social, economic, technological, and systems perspectives. *Clean Technology and Environmental Policy, 5*, 167–180.

Caruso, G., Rounsevell, M., & Cojocaru, G. (2005). Exploring a spatio-dynamic neighbourhood-based model of residential behaviour in the Brussels periurban area. *International Journal of Geographical Information Science, 19*(2), 103–123.

Chin, N. (2002). *Unearthing the roots of urban sprawl: A critical analysis of form function and methodology*. *Centre for Advanced Spatial Analysis (CASA) Working Paper Series*. London: University College London.

Clarke, K. C. (2005). The limits of simplicity: Toward geocomputational honesty in urban modeling. In P. Atkinson, G. Foody, S. Darby, & F. Wu (Eds.), *GeoDynamics*. Boca Raton: CRC Press.

Deadman, P., Robinson, D. T., Moran, E., & Brondizio, T. (2004). Colonist household decisionmaking and land-use change in the Amazon Rainforest: An agent-based simulation. *Environment and Planning B: Planning and Design, 31*(5), 693–709.

Deakin, M., Mitchell, G., Nijkamp, P., & Vreeker, R. (2007). *Sustainable urban development. The environmental assessment methods* (vol. 2). New York: Routledge.

Department of Energy (2005). *Average residential monthly use (of electricity)* (cited March 28, 2007). <http://www.eia.doe.gov/neic/quickfacts/quickelectric.html>.
Downs, A. (1994). *New visions for metropolitan America*. Washington, DC/Cambridge: The Brookings Institution/Lincoln Institute of Land Policy.
Ducrot, R., Le Page, C., Bommel, P., & Kuper, M. (2004). Articulating land and water dynamics with urbanization: An attempt to model natural resources management at the urban edge. *Computers, Environment and Urban Systems, 28*(1–2), 85–106.
Ehrenhalt, A. (2000). Sprawl, passion and common sense. *Governing Magazine*. April.
Ewing, Reid H. (1994). Characteristics, causes and effects of sprawl: A literature review. *Environmental and Urban Issues, 21*(2), 1–15.
Ewing, Reid H. (1997). Is Los Angeles-style sprawl desirable? *Journal of American Planning Association, 63*(1), 107–126.
Fath, B., Cabezas, H., & Pawlowski, C. (2003). Regime changes in ecological systems: An information theory approach. *Journal of Theoretical Biology, 222*(4), 517–530.
Fisher, R. A. (1925). *Theory of statistical estimation*. *Proceedings of the Cambridge Philosophical Society*. Cambridge: Cambridge University Press.
Frieden, B. R. (2004). *Science from Fisher information: A unification*. Cambridge, UK: Cambridge University Press.
Garde, Ajay M. (2004). New urbanism as sustainable growth? A supply side story and its implications for public policy. *Journal of Planning Education and Research, 24*(2), 154–170.
Garreau, J. (1991). *Edge city*. New York: Anchor Books.
Gordon, P., & Richardson, H. W. (2000). Defending Urban Sprawl. *Public Interest*(Spring).
Guindon, B., & Zhang, Y. (2007). Using satellite remote sensing to survey transport-related urban sustainability Part II. Results of a Canadian urban assessment. *International Journal of Applied Earth Observation and Geoinformation, 9*, 276–293.
Hanley, P. F., & Hopkins, L. D. (2007). Do sewer extension plans affect urban development? A multiagent simulation. *Environment and Planning B: Planning and Design, 34*(1), 6–27.
Heilbrun, J. (1987). Urban economics and public policy. *3rd ed.*. New York: St. Martin's Press.
Henderson, R., & Moore, A. T. (1998). Plan obsolescence. *Reason, 30*(2).
Hirsch, W. Z. (1984). *Urban economics*. New York: Macmillan Publishing Company.
Hoffman, M., Kelley, H., & Evans, T. (2003). Simulating land-cover change in South-Central Indiana: An agent-based model of deforestation and afforestation. In M. Janssen (Ed.), *Complexity and ecosystem management: The theory and practice of multi-agent approaches*. Northampton, MA: Edward Elgar Publishers.
Holland, J. H. (1995). *Hidden order: How adaptation builds complexity*. Helix Books: Addison-Wesley Publishing Company.
Karunanithi, A. T., Cabezas, H., Frieden, R., & Pawlowski, C. (2008). Detection and assessment of ecosystem regime shifts from Fisher information. *Ecology and Society, 13*(1), 22. Available from: <http://www.ecologyandsociety.org/vol13/iss1/art22/>.
Lee, Douglass B. Jr., (1973). Requiem for large-scale models. *Journal of the American Institute of Planners, 39*, 163–178.
Manson, S. (2007). Challenges in evaluating models of geographic complexity. *Environment and Planning B: Planning and Design* [advance online publication].
Mayer, A., Pawlowski, C., & Cabezas, H. (2006). Fisher information and dynamic regime changes in ecological systems. *Ecological Modeling*.
Mayer, A., Thurston, H., & Pawlowski, C. (2004). The multidisciplinary influence of common sustainability indices. *Frontiers in Ecology and the Environment, 2*(8), 419–426.
McKee, D. L., & McKee, Y. A. (2001). Edge cities and the viability of metropolitan economics: Contributions to flexibility and external linkages by new urban service environments. *American Journal of Economics and Sociology, 60*(1).
Miller, J. H., & Page, S. E. (2007). *Complex adaptive systems: An introduction to computational models of social life*. Princeton, NJ: Princeton University Press.
Neuman, Michael. (2005). The compact city fallacy. *Journal of Planning Education and Research, 25*(1), 11–26.
Norton, Richard K. (2007). Planning for school facilities: School board decision making and local coordination in Michigan. *Journal of Planning Education and Research, 26*(4), 478–496.
O'Sullivan, D., & Torrens, P. M. (2001). Cellular automata and urban simulation: Where do we go from here? *Environment and Planning B: Planning and Design, 28*, 163–168.
Parker, D. C., Manson, S. M., Janssen, A., Hoffman, M., & Deadman, P. (2003). Multi-agent systems for the simulation of land-use and land-cover change: A review. *Annals of the Association of American Geographers, 93*(2), 314–337.
Parker, D. C., & Meretsky, V. (2004). Measuring pattern outcomes in an agent-based model of edge-effect externalities using spatial metrics. *Agriculture, Ecosystems & Environment: From Pattern to Process: Landscape Fragmentation and the Analysis of Land Use/Land Cover Change, 101*(2–3), 233–250.
Pawlowski, C., Fath, B., Mayer, A., & Cabezas, H. (2005). Towards a sustainability index using information theory. *Energy, 30*(8), 1221–1231.
Rand, W., Zellner, M. L., Page, S. E., Riolo, R. L., Brown, D. G., & Fernandez, L. E. (2002). *The complex interaction of agents and environments: An example in urban sprawl*. Paper read at Agent 2002 conference on social agents: Ecology, exchange and evolution, at Chicago, IL.
Rees, W. (1996). Revisiting carrying capacity: Area-based indicators of sustainability. *Population & Environment, 17*(3), 195–215.
Sadownik, B., & Jaccard, M. (2001). Sustainable energy and urban form in China: The relevance of community energy management. *Energy Policy, 29*, 55–65.
Torrens, Paul M. (2006). Simulating sprawl. *Annals of the Association of American Geographers, 96*(2), 248–275.
University of Michigan (2001). *Detroit Area Study 2001* [cited. <www.tcaup.umich.edu/workfolio/DAS2001/stdescript.html>.
US Environmental Protection Agency (2006). *Clean Energy: Air Emissions.* [cited April 16, 2007. <http://www.epa.gov/cleanenergy/emissions.htm>.
van de Coevering, P., & Schwanen, T. (2006). Re-evaluating the impact of urban form on travel patterns in Europe and North-America. *Transport Policy, 13*, 229–239.
Yin, L., & Muller, B. (2007). Residential location and the biophysical environment: Exurban development agents in a heterogeneous landscape. *Environment and Planning B: Planning and Design* [advance online publication].
Zellner, M. L. (2007). Generating policies for sustainable water use in complex scenarios: An integrated land-use and water-use model of Monroe County, Michigan. *Environment and Planning B: Planning and Design, 34*(4), 664–686.